Renewable and Sustainable Energy Reviews 15 (2011) 2677–2683

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

Assessing the effect of wind power uncertainty on profitability

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A R T I C L E I N F O

Article history:
Received 20 December 2010
Accepted 30 January 2011

Keywords:
Wind power
Bootstrapping
Measure-Correlate-Predict Method
Conditional Value at Risk
Internal Rate of Return

A B S T R A C T

Wind energy has been the fastest growing and most promising renewable energy source in terms of profitability in recent years. The annual installed capacity in the European Union (EU) has risen from 814 MW in 1996 to 10,163 MW in 2009. However, one major drawback of wind energy is the variability in production due to the stochastic nature of wind. Integrating the risk of wind energy uncertainty into profitability assessments is important for investors in wind energy. The article presents statistical simulation methods to incorporate risks from stochastic wind speeds into profitability calculations. We apply the Measure-Correlate-Predict (MCP) Method within the Variance Ratio Method to generate long-term wind velocity estimates for a potential wind energy site in Austria. The bootstrapping method is applied to generate wind velocities for the economic life-time of a wind turbine. The Internal Rate of Return is used as profitability indicator. We use the Conditional Value at Risk (CVaR) approach to derive probability levels for certain internal rate of returns, as the CVaR is a reliable risk measure even if return distributions are not normal. Our approach closes the gap in the scientific literature on statistical simulation methods for the economic evaluation of wind energy sites. In contrast to other scientific publications, our methodology can be generally applied, because we do not rely on estimated distributions for wind speed predictions, but on measured wind speed distributions, which are usually readily available. In addition, the CVaR has not been applied as a measure of risk for wind site evaluation before and it does not rely on any specific function regarding the profitability distribution. The approach has been developed in collaboration with a leading Austrian utility company and has been applied to a wind park in Austria.

Contents

1. Introduction

Wind energy was the fastest growing renewable energy resource in the European Union (EU) in the last decade. The annual installed capacity has risen from 814 MW in 1996 to 10,163 MW in 2009 [1]. In 2009, approx. EUR 13 billion, including EUR 1.5 billion offshore were invested in wind energy in the EU [1]. In this respect, the wind power capacity shall reach approx. 80 GW by 2010 becoming the renewable energy technology with the highest installed capacity in the EU, second only to hydro power [1]. In 2009, approx. 5.4% of the electricity consumption was produced with wind energy in the EU. It is projected that the contribution of wind energy to total electricity consumption within the EU will increase to approx. 15.5% in 2020 [2].

The stochastic nature of wind leads to fluctuations in wind energy production. The literature concerning wind speed uncer-

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doi:10.1016/j.rser.2011.01.024

tainty can be divided, for instance, into literature focusing on uncertainty in wind energy output and on economic profitability. With respect to uncertainty in wind energy output, Kwon [3] has elaborated a numerical procedure for evaluating the uncertainty caused by wind variability and power performance using probability models in order to assess the risk of power output deviations. He conducted a case study analysis to show that the standard deviation of the annual energy output normalized by the average value of power output is approx. 11%, which can cause investments to be unprofitable. Tindal et al. [4] have compared the predicted annual power production with the actual power production. Their dataset included 510 wind farms across Europe and the US. They showed that the actual wind power output is 93.3% of the predicted wind power output. According to the authors, a major reason for this deviation is the rather poor quality of wind speed measurements which have been conducted before the installation of wind turbines.

A number of articles have statistically analysed wind speed data by assessing the wind energy potential in a certain region (e.g. [5–11]). Thereby, the economic potential and profitability have been identified by applying traditional methods of financial analysis such as the Net Present Value approach, the Internal Rate of Return approach, or the Life Cycle Cost Analysis approach.

Morthorst [12], for example, analysed whether there is a relationship between the expected profitability of a wind turbine and the annual increase in installed capacity in Denmark. He used the net Internal Rate of Return approach (after tax) as a measure for profitability. Kaldellis and Gavras [13] conducted a sensitivity analysis in order to show the impact of different parameters on the economic viability and attractiveness of a wind energy plant. However, Montes and Martin [14] argue that statistical simulation methods should be used to account for and assess the economic risk resulting from the variability in wind speed.

Some authors analyse the wind energy potential of a specific site by using either Monte Carlo simulations for predicting wind speeds or by using the wind speed measurement data directly if sufficient measurement data are available [3,9,15–17]. However, Monte Carlo simulations require assumptions with respect to the distribution of the wind speeds. Consequently, Carta et al. [18] concluded that not every wind regime can be accurately described with known probability distributions.

The following article presents an approach that accounts for the uncertainty of wind speed in profitability assessments. The approach can easily be applied for any actual and potential wind energy site without specifying the distributions of wind speed. The article is structured as follows: Section 2 presents the methodology. Section 3 presents a case study analysis in which the methodology has been applied to and Section 4 discusses the results and draws major conclusions from the methodology and analysis.

2. Methodology

Our approach consists of generating long-term wind speed data for a potential wind energy site ('target site') where only short time series of wind measurement data are available using the Measure-Correlate-Predict (MCP) algorithm with wind speed data from a reference site (Fig. 1). A bootstrapping procedure is applied to compute wind speed data for the economic life-time of the wind turbine. The Internal Rate of Return approach is used as profitability index. The bootstrapping procedure allows more accurately reflecting the distribution of the wind regime in the predicted wind speeds than methods currently applied in the scientific literature on wind energy production. Furthermore, the bootstrapping procedure can be applied to any wind regime. As a measure of risk we use the Conditional Value at Risk ('CVaR') approach. The CVaR can be uniformly applied and is not only appropriate if returns are normally distributed [19]. The CVaR also provides information at which probability level a certain Internal Rate of Return can be expected.

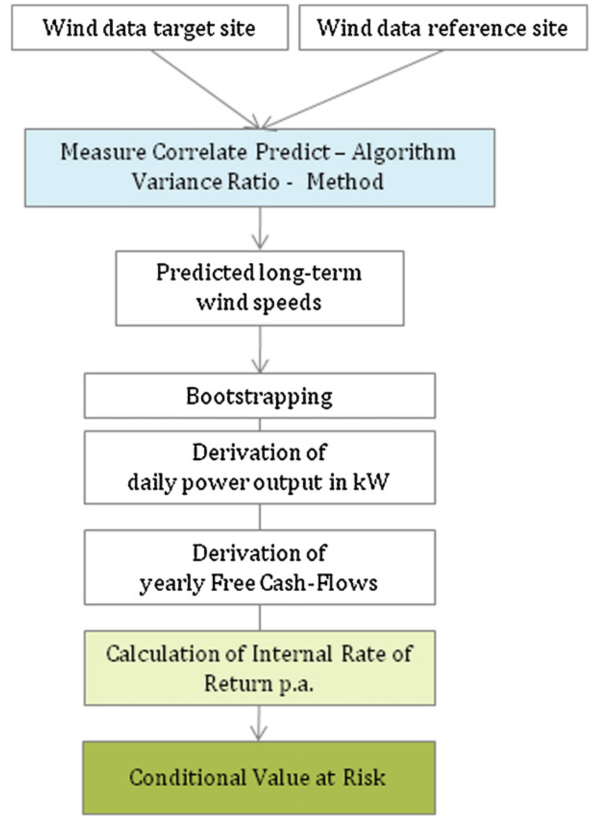

Fig. 1. Overview of the methodology.

2.1. Assessment of the wind energy potential at a specific site

Wind speed measurement data are usually collected at a specific site (target site) through a period of one year or less. Wind speed frequency distributions are computed from the data in order to estimate a probability density function. Several probability density functions have been used in the literature, but the two-parametric Weibull and the one-parametric Rayleigh distribution, which is a special case of the Weibull distribution, are usually used to predict wind speeds [3,13,15,16]. The two-parametric Weibull probability density function is given by the following equation [9]:

$$f(V) = \frac{k}{c}\left(\frac{V}{c}\right)^{k-1} \exp\left\{-\left(\frac{V}{c}\right)^{k}\right\}, \quad 0 < V < \infty \tag{1}$$

where c and k are the scale and shape parameters and V the wind speed. The shape parameter k is usually between 1.5 and 3.0. If the value of the shape parameter is 2.0, the distribution is called Rayleigh distribution. The probability density function of the Rayleigh distribution is shown in Eq. (2) [9]:

$$f(V) = \frac{2V}{c^2} \exp\left\{-\left(\frac{V}{c}\right)^{k}\right\} \tag{2}$$

The review by Carta et al. [18] shows that the two-parametric Weibull distribution has several advantages compared to other probability density functions proposed in the scientific literature. However, not every wind speed regime can be described by a probability distribution. Therefore, the bootstrapping procedure does not require any assumptions on the distribution of the wind speed [18,20]. However, long-term wind measurement data are needed

for the target site. As already indicated, wind measurement data are usually collected through a period of one year or less. We apply the Measure-Correlate-Predict (MCP) algorithm to estimate long-term wind speed data for a target site using wind data from a reference site.

We use long-term wind data from a closely located meteorological station as reference site. According to [22], the MCP algorithm in the form of the Variance Ratio Method gives consistent and reliable estimates of wind speeds. The relationship between the wind speed data at the reference site and the wind speed at the target site can be expressed by the following equation [22]:

$$\hat{V}_t = \left(\mu_t - \left(\frac{\sigma_t}{\sigma_r}\right)\mu_r\right) + \left(\frac{\sigma_t}{\sigma_r}\right)V_r \qquad (3)$$

where $\hat{V}_t$ is the predicted long-term wind speed at the target site, V_r is the long-term wind speed at the reference site and μ_t, μ_r, σ_t and σ_r are the mean and the standard deviation of the target and the reference site, respectively.

If wind measurements have not been conducted at hub height, the measured wind speeds have to be adjusted to hub height. We apply the following equation [10]

$$V_{hub} = V_m \frac{\ln(h_{hub}/z)}{\ln(h_m/z)} \qquad (4)$$

where V_{hub} defines the wind speed at hub height, V_m the wind speed at measurement height, V_{hub} and h_m are the height of the hub and the measurement facility, and z is the roughness length [23]. The respective surface roughness at a specific site strongly depends on the terrain conditions.

The actual power output $P(V)$ of a wind turbine can be expressed by the following equation [9]:

$$P(V) = \int_{V_{in}}^{V_n} \frac{1}{2} cp \cdot \rho \cdot V^3 \cdot \pi \cdot \left(\frac{D}{2}\right)^2 + \int_{V_n}^{V_{out}} P_t \qquad (5)$$

where V_n defines the rated wind speed, V_{in} the cut-in wind speed, cp the capacity factor, ρ the air mass density, V the wind speed, D the rotor diameter, V_{out} the cut-out wind speed and P_t the rated power output. A wind turbine starts generating power at the cut-in wind speed (V_{in}). From the cut-in wind speed to the rated wind speed (V_n), the power generated continuously increases up to the nominal power of the wind turbine. The turbine produces constantly electricity at its rated power from the rated wind speed to the cut-out wind speed (V_{out}).

2.2. Profitability calculations

The economic evaluation of investment projects is usually based on the Discounted Cash Flow (DCF) approach [24]. The approach provides information about the value of a project based on the present value of the cash flows that the project can be expected to generate in the future (cash in- and outflows). In the case of wind energy, cash inflows result from the electricity sold and cash outflows are investment and operating expenses. Operating expenses are mainly maintenance costs, personnel expenses, insurance costs, land lease, etc. [25]. Cash in- and outflows are discounted to reflect the time and risk preferences of the decision maker associated with the cash flows. The DCF method comprises the following steps:

- estimating future cash flow for a certain discrete projection period and
- discounting these cash flows to the present value at a rate of return that considers the relative risk of achieving the cash flows and the time value of money.

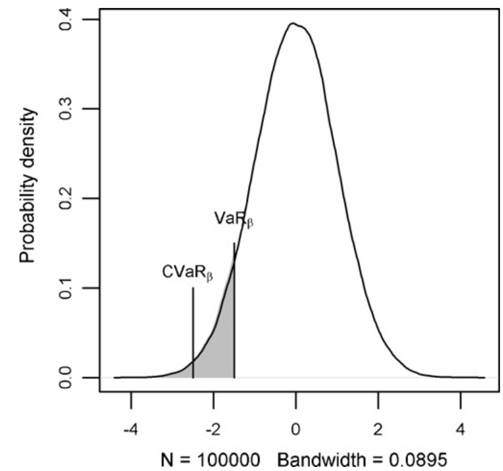

Fig. 2. Difference between the VaR and the CVaR.

Therefore, the Net Present Value (NPV) of a wind power project can be written as follows:

$$\mathrm{NPV} = \sum_N CF_n (1+r)^{-n} \qquad (6)$$

where n is the number of years, CF_n the cash flow in the corresponding year and r is the discount rate reflecting the preferences of an investor.

The financial attractiveness of wind energy investment projects is usually measured by the NPV and/or the Internal Rate of Return (IRR) [11,12,21,26]. Investors are usually interested in the maximum NPV for a preferred discount rate of future cash flows. The IRR provides the discount rate at which NPV is equal to zero such that it can also be defined as the return that the project is going to generate considering cash out- and in-flows. A project can be stated to be economically viable, if the IRR is at least above the risk free rate or, if the NPV is equal or greater than zero. Eq. (7) defines the IRR [24]:

$$\begin{aligned} \mathrm{NPV} = 0 &= CF_0 + \frac{CF_1}{(1+IRR)^1} + \frac{CF_2}{(1+IRR)^2} + \cdots + \frac{CF_n}{(1+IRR)^n} \\ &= \sum_{t=0}^{n} \frac{CF_t}{(1+IRR)^{t'}} \end{aligned} \qquad (7)$$

where CF_t is the cash flow in the corresponding year.

2.3. The Conditional Value at Risk (CVaR)

We apply the CVaR as a measure of risk. Since the Value at Risk (VaR) as well as the variance as risk measures provide only reliable results if the underlying events are normally distributed [19,27], CVaR does not require a normal distribution of events and considers especially the tails of the underlying distribution [19,27]. The CVaR and the VaR are closely related, therefore we describe the VaR first. The VaR states that with probability β the expected value will not be lower than a certain threshold α. The CVaR focuses on the tails of the distribution and averages the values which fall short of threshold α depending on the probability level β. Therefore, the CVaR is a more conservative risk measure. Fig. 2 illustrates the difference between the VaR and the CVaR.

3. Case study analysis

The wind measurement data from a wind turbine site in Styria (Austria), which is in operation since 2005, have been used in our

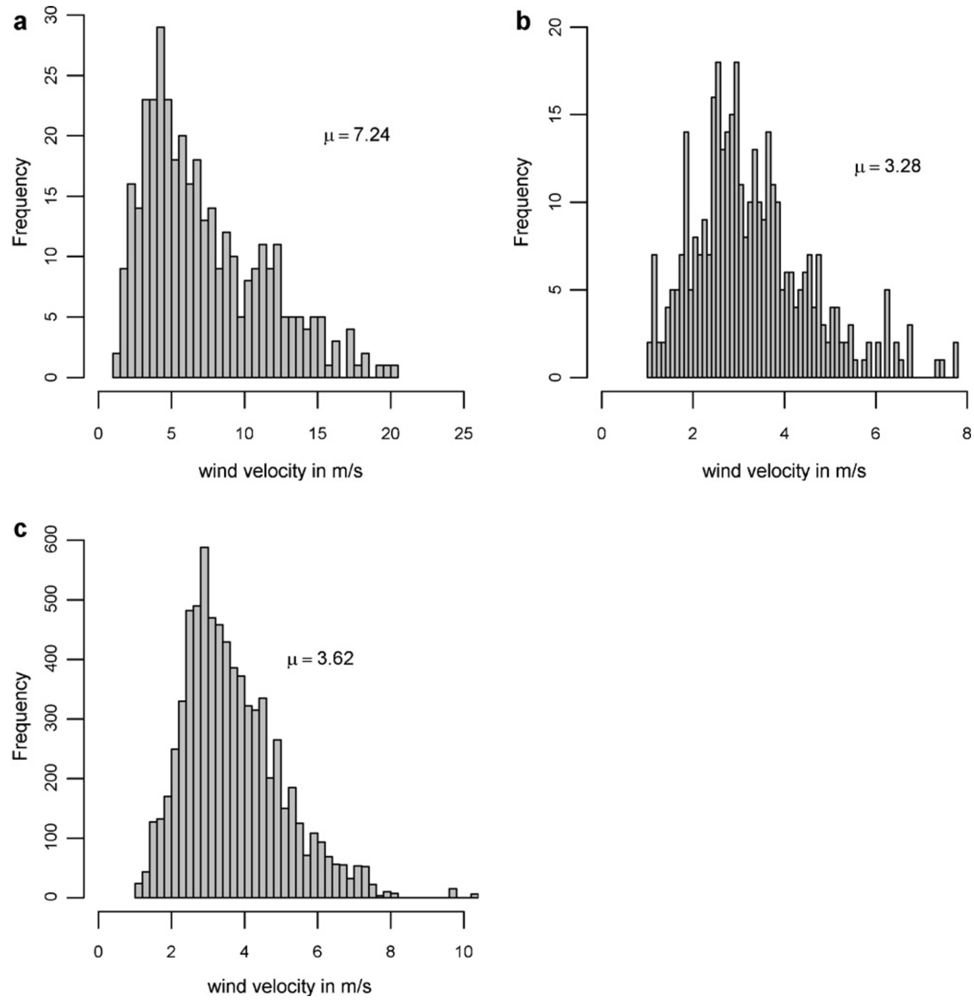

Fig. 3. Histogram of daily mean wind velocities: (a) daily mean wind velocities at the target site for the year 2007; (b) daily mean wind velocities at the reference site for the year 2007; (c) daily mean wind velocities at the reference site for the years 1990–2009.

case study analysis. The data set consists of hourly mean wind speeds as well as of hourly mean power output for the years 2006–2008. The hourly mean wind speeds of the year 2007 have been used as target site data. The data from a meteorological station (reference station) includes daily mean wind speeds for the years 1990–2009. Therefore, the calculations are based on daily mean wind speeds using the daily average of hourly wind speed measurement data of the target site. We use data from 2007 for the application of the MCP method. The different wind velocities are shown in Fig. 3, where Fig. 3a shows the daily mean wind velocities at the target site for the year 2007, Fig. 3b shows the daily mean wind velocities at the reference site for the year 2007, and Fig. 3c shows the daily mean wind velocities at the reference site for the years 1990–2009. The correlation between the hourly mean wind velocity at the target site and the hourly mean wind velocity of the reference site is shown in Fig. 4a. The correlation equation derived from Eq. (3) is as follows:

$$\hat{V}_t = -3.7507 + 3.3065\, V_r \tag{8}$$

The long term wind velocities at the target site are estimated on the basis of the slope and the intercept of Eq. (8). However, before applying the MCP method, the wind speed at the reference station has to be extrapolated from the anemometer to hub height using Eq. (4). As the target site is located in mountainous area, the correlation between the target and the reference site is low (0.2120). According to the utility manager (oral communication), the reference station has been used to evaluate the target station before deciding on the construction of the wind park. Therefore, we also use the same reference station in our case study analysis. The daily wind measurement data at the reference site record a period of 20 years such that long-term daily mean wind velocities are computed for this period with the MCP method.

Currently, the feed-in tariffs are guaranteed for a period of 13 years in Austria. Therefore, we assume that a potential investor requires a certain return of investment within the period in which he or she receives a guaranteed electricity price. Our calculations concerning the profitability assessment are based on a 13-year period of predicted daily mean wind velocities. Seasonal differences are reflected in the bootstrapping procedure, which has been repeated 1000 times. Consequently, several trajectories are obtained both for the wind speeds and the power outputs. The trajectories are also used in the statistical evaluations revealing information that are relevant for investment decisions. The probability density distributions of the generated wind speeds via bootstrapping (1000 trajectories) and the wind speed measurement data at the target site in 2007 are shown in Fig. 4b.

The energy power output is derived for a 1.3 MW wind turbine with a turbine diameter (D) of 62 m, a cut-in wind speed (V_{in}) of 4 m/s, a cut-out wind speed (V_{out}) of 25 m/s, and a rated wind speed (V_n) of 13 m/s, respectively. The capacity factor (cp), which is defined as the ratio of the energy generated to nominal energy generation is 0.4. The air mass density (ρ) corresponds to 1.27 kg/m^3.

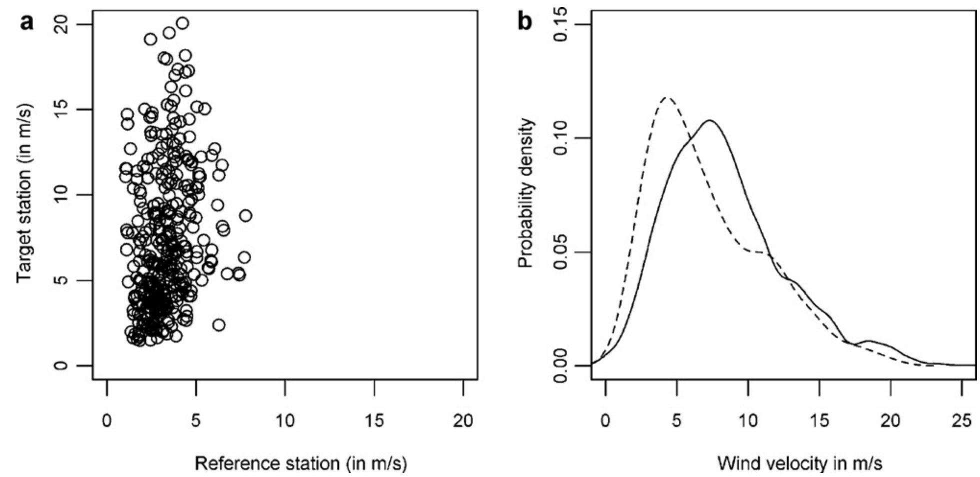

Fig. 4. (a) Comparison between the daily mean wind velocities at the target and reference site; (b) probability density function of the wind speeds generated by the bootstrap procedure (1000 trajectories) and wind speed measurement data at the target site (dotted line) in 2007.

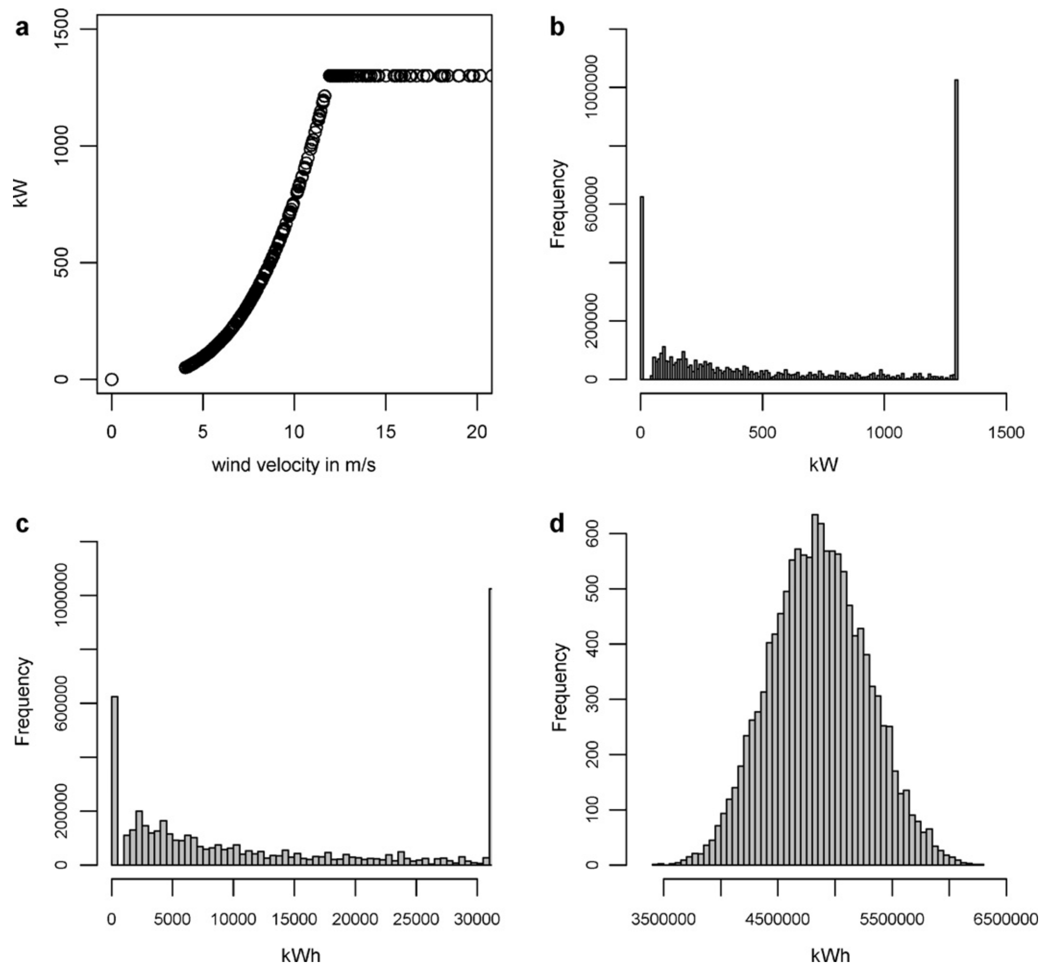

Fig. 5. (a) The power curve of a 1.3 MW wind turbine; (b) histogram of computed power output; (c) histogram of the daily generated electricity in kWh; (d) histogram of the annual generated electricity in kWh.

Fig. 5a shows the computed power curve for the generated wind speeds via bootstrap corresponding to one year.

The histogram of the power output is shown in Fig. 5b. The high frequency of 0 kW and 1300 kW power output is due to the fact that the wind turbine starts producing power at a wind speed of 4 m/s and reaches its rated wind speed at 13 m/s. The daily generated electricity production can be computed by multiplying the computed power output with 24 (hours of a day). The daily generated electricity production is then added up to annual generated electricity production as profitability calculations are conducted on annual time steps.

The histogram of the daily and annual generated electricity in kWh is shown in Fig. 5c and d, which follows a normal distribution according to the central limit theorem. The theorem states

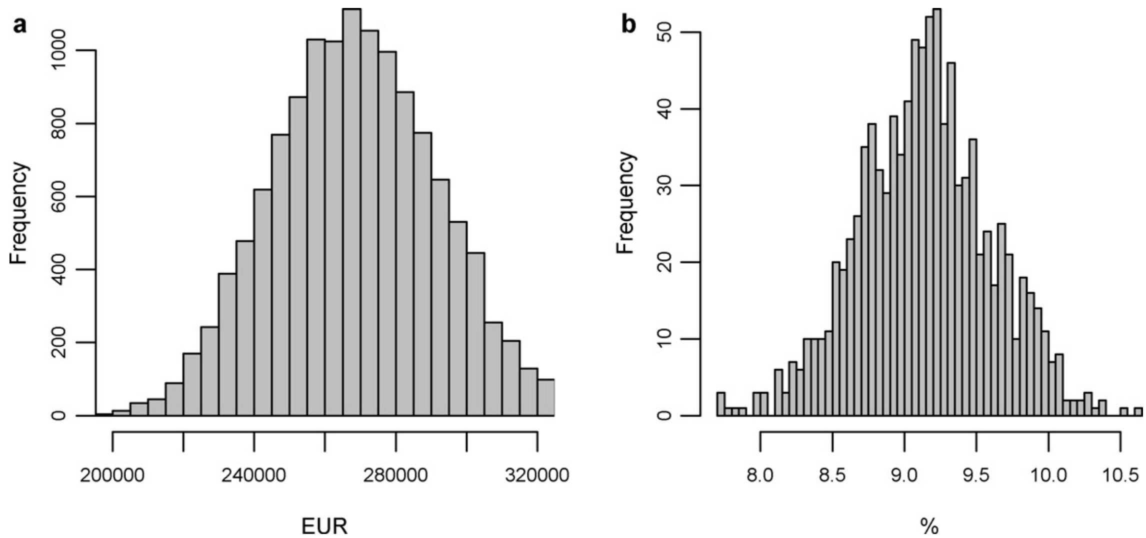

Fig. 6. (a) Histogram of the generated FCF; (b) histogram of IRR.

that the probabilities of events generated with the sum of independent, identical distributed random variables X approximate to a normal distribution for a sufficiently large number of events. The central limit theorem indicates that the distribution of $\sum X_i$ for an increasing n approaches always the $N(n\mu; \sigma\sqrt{n})$ distribution [28].

The annual Free Cash Flows (FCFs) can be derived from the annual generated electricity. The cash inflows result from the generated electricity, which is sold at the guaranteed feed-in tariff that currently amounts to 0.0753 EUR/kWh in Austria. The cash outflows are the investment costs for the wind turbine, which are

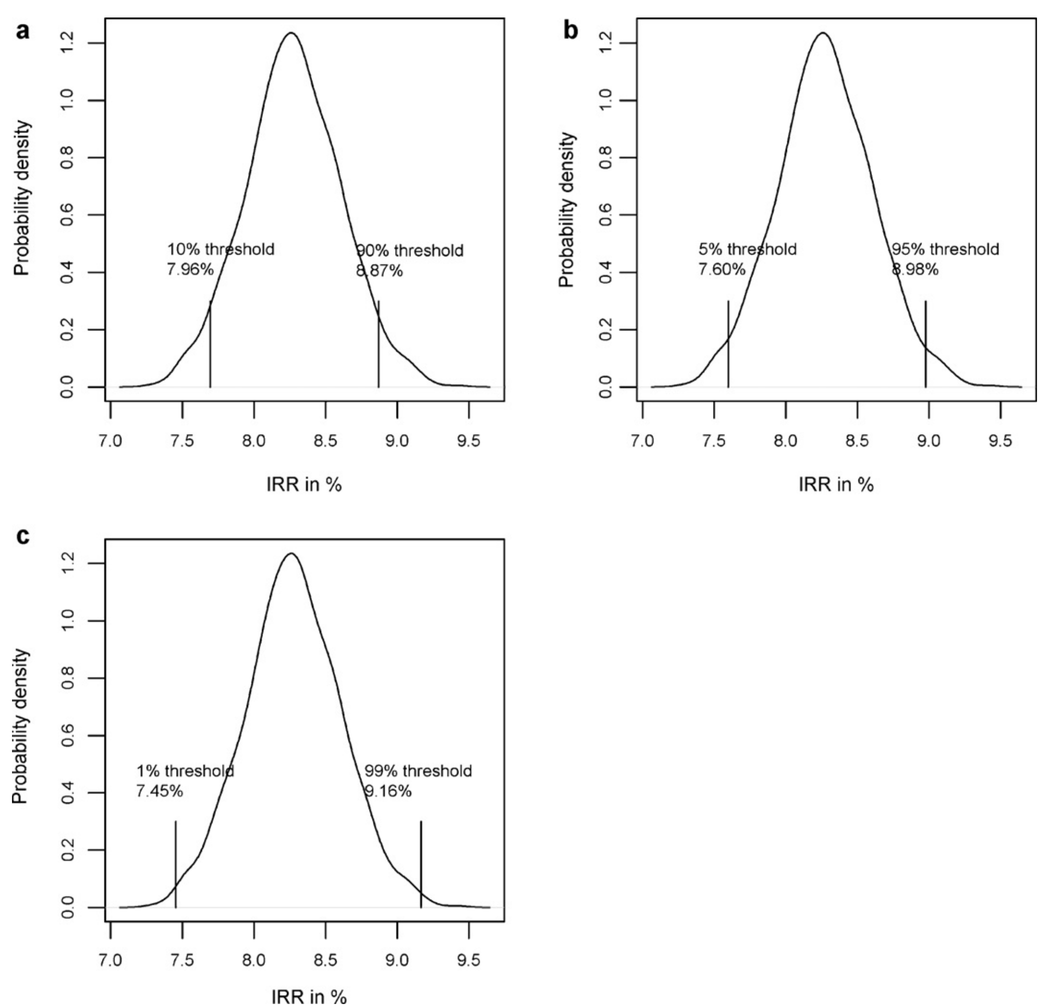

Fig. 7. Probability density functions of the IRR and the CVaR. (a) Probability density function of the IRR with the threshold levels of 10% and 90%; (b) probability density function of the IRR with the threshold levels of 5% and 95%; (c) probability density function of the IRR with the threshold levels 1% and 99%.

EUR 1.5 mil. per MW installed according to the provider of the wind measurement data. The operating costs are amounting to 0.020 EUR/kWh. Further corporate tax payments have to be considered when calculating the FCFs (the current corporate tax rate is 25% in Austria). It is assumed that demolition costs at the end of the lifetime equal the revenue which can be generated out of selling the steel from the wind turbine. The histogram of the resulting FCF is shown in Fig. 6a.

The Internal Rate of Return has been calculated from the computed annual FCF. A standard criterion for investment decisions is the hurdle rate. It reflects a discounting rate at which the investments provide a positive cash flow. If a negative NPV results out of discounting the FCF with the hurdle rate, the underlying investment will most likely not be approved by the management [29]. Consequently, an investment can be approved if the IRR exceeds the hurdle rate. Fig. 6b shows the histogram of the Internal Rate of Return in our case study analysis.

3.1. The Conditional Value at Risk

The probability density functions are shown for different risk aversion levels in Fig. 7. The IRR will be not lower than 7.96% at a probability level of $\beta = 90\%$ according to the probability density function of the IRR shown in Fig. 7a. If the hurdle rate for an investor is above 7.96% then an investor shall not decide against the investment. However, the investor might realize an IRR above 8.87% with a 10% probability. Fig. 7b and c show the resulting IRRs for different probability levels.

4. Concluding remarks

We have developed a methodology to better assess the profitability of a wind energy site in the presence of wind speed uncertainty. Our approach can be applied to any wind regime. We apply statistical simulation methods to close the gap in the scientific literature on wind energy production [14]. Neither the bootstrapping method to predict wind speeds nor the Conditional Value at Risk approach have been applied for investment assessments in combination with wind site evaluations. We have combined and applied these methods for a case study analysis. For a 1.5 MW wind turbine with investment costs of EUR 1.5 mil. per MW and operating expenses of 0.020 EUR/kWh, the IRR with a probability of 95% will not be lower than approx. 7.60% for the case study wind energy site. With a 5% probability, however, an investor can achieve an IRR above of 8.98%.

Acknowledgements

This article has been supported by the project “Towards the 2020 climate and energy goals: cost-effective policy instruments for CO_2 emission reduction and renewable energy support in Austria” funded by the “Jubiläumsfonds” of “Österreichische Nationalbank” as well as by the project “Energieversorgung aus Land- und Forstwirtschaft in Österreich unter Berücksichtigung des Klima- und Globalen Wandels in 2020 und 2040 (Energ.Clim)”.

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